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A Fuzzy-Bayesian Model for Risk Assessment in Power Plant Projects

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Abstract

Cost overrun in power plant projects is a global problem. Assessing potential risks at preliminary stage of the project is important to control cost overrun. Existing models are discovered as ineffective for assessing cost overrun risks in power plant projects due to two basic limitations- i) incapable to handle subjective biases in riskassessment and ii) complex relationship among the risk factors. A novel method based on the combination of fuzzy logic and Bayesian belief network has been developed, which can solve both drawbacks of the existing models and provides the best result for finding inherent risks in power plant projects. This model assists the project managers providing early warning to manage the critical risks. It also helps to reach a realistic budget considering the costs of potential and critical risks in the estimation process, which consequently reduces the cost overrun of power plant projects.

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*Keywords:*Bayesian belief network; cost overrun; fuzzy logic; power plant projects; risk assessment

1. Introduction

Cost overrun is afrequently occurring phenomenon in power plant construction projects globally[1]. A recent study[2] revealed that average cost overrun in power plant construction projects in Europe and North America is about

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200%. The research identified many causes to produce project cost overrun, for example, estimation inaccuracy, project complexity and improper risk assessment and management[3–6]. The estimating accuracy largely depends on the certainty of available information as well as the estimator's clear understanding of the project regarding design, construction methods, project risks, available resources, and many other contextual factors and constraints[7]. The project complexity and improper risk assessment are often considered as the foremost factors of estimation inaccuracy, which subsequently leads to cost overrun of a project[3]. A complex project consists of many interdependent activities, which potentially increase the risks and uncertainties[8,9]. The power plant project consists of highly complex mechanical, electrical and civil works along with interrelated technical, environmental and socio-political issues. As such, it is not surprising that cost overrun scenarios are often the norms rather than exceptions in the power plant industry[1].

Evaluating potential risks are very important to control project cost overruns[10–12]. There are many advanced methods available for project risk assessment, such as fuzzy logic, analytical hierarchy process (AHP), analytical network process (ANP), failure mode and effect analysis (FMEA), fault tree, event tree, fish-born diagram, Monte Carlo simulation (MCS) and structural equation model (SEM)[13–16].These methods are influenced by subjective judgments and provide poor results for assessing risks because risks analysts in the power plant project mostly depends on their judgements based on the previous knowledge and experiences. Except SEM, other methods do not systematically capture the causal relationships of project risks, which are very important for proper risk assessment. While SEM-based risk assessment method shows a causal relationship between risks and their level of significance[17], it defines the impacts of risks as a crisp value rather than a "fuzzy" number. The risk is more understandable as a fuzzy number than a crisp value[16]. Existing risk assessment methods define risk at a higher conceptual level with a particular focus on the entire lifecycle of a construction project. But risks in complex projects are interdependent in many cases[17]and their causal relationships are more understandable as risk breakdown structure under major work packages of construction projects. Bayesian belief network (BBN) is considered superior to other methods as it can handle probabilistic causal relationships of risks found from the domain experts' judgements and can update previous beliefs and probabilities learning from the new information[18,19].The power plant project is a complex system, in which there are numerous inter-dependencies among the risk factors in a fuzzy concept. Therefore, this study aims to develop a fuzzy-Bayesian model for risk assessment to reduce cost overrun in power plant projects. To develop this model, a literature review has been done finding the drawbacks of previous methods and studying the nature of cost overrun risks in power plant projects. These issues are then addressed in the developed model considering the appropriate applications of fuzzy logic and Bayesian belief network. Finally, an example is presented to demonstrate the model.

This paper is organized as follows: Section 2 briefly discusses the basic concepts of fuzzy logic and Bayesian belief network; Section 3 introduces the proposed fuzzy-Bayesian risk assessment model; Section 4 presents an example for demonstrating the model; and Section 5 contains the concluding remarks.

2. Concepts of fuzzy logic and Bayesian belief network

Fuzzy logic is a very effective management technique to achieve the objectives of the construction project under uncertainties, impression, and biasness[20]. It can be used to develop a model on the basis of data found as qualitative terms from experts' judgements and quantitative values from historical records[21]. Construction risks are still managing based on experts' judgments and experiences[22]. Therefore, the data type for risk studies is mostly qualitative rather quantitative. Due to its suitability for qualitative data analysis, fuzzy logic has been used in risk assessment for a long time. Fuzzy logic contains the following basic steps: (1) define and measure the risk likelihood of occurrence and severity in terms of verbal opinion, and transfer them into fuzzy numbers accordingly; (2) define the fuzzy inference to make a network between input and output parameters using suitable "fuzzy arithmetic operators"; and (3) defuzzification of the fuzzy outcomes into numerical values[23]. However, in a complex project, the risks are materialized by many interrelated factors with uncertain relationships[24]. Fuzzy logic based risk assessment methods do not capture the uncertain causal relationship of risks under different work packages of power plant projects. These relationships among the risk factors can be graphically presented by the networks, called risk networks. In the risk networks, there are nodes and edges where the nodes represent the risk factors (i.e., dependent or independent variables) and the edges (arrows) show the direction of inter-dependencies between the risks.

Nonetheless, the simple risk networks do not represent the degrees of dependencies and causal relationships between the risks of very complex and uncertain projects. Bayesian belief network (BBN) is one of the suitable means of risk analysis that can solve these complex and uncertain dependencies/relationships in the risk networks[25]. The BBN is graphically defined by directed acyclic graph (DAG) where nodes represent variables (risks) and arrows depict the causative relationships among the variables (risks). Besides, the arrows grasp the uncertainties inside the networks, which are mutually inclusive using the concept of conditional probabilities[26,27]. It is also a very easy approach to construct large and complex risk networks by using the aggregation process of sub-networks in hierarchy levels[28].

Two types of probabilistic data are required to solve any Bayesian network, for example, prior probability of independent risk (variable) and conditional (effect as the influence of cause) probability of dependent risk given that of independent or preceding risk. Then, following the Bayesian probability theory, it is easy to find the risk probability of the dependent risk[25]. In the case of hierarchy levels of risks, this network gives the opportunity to reduce the needs of collecting huge data because it helps to compute the probabilities of the upper level of dependent variables from the available probabilistic data of preceding factors (i.e. prior probability) and the probabilistic dependencies (i.e. conditional probability). Additionally, previous studies recommend that this method is a suitable and powerful tool to work with an inadequate and poor number of data sets, data found from a mixture of different areas of knowledge, non-parametric and distribution free data, and data of highly diversified variables[25,29]. BBN can easily update the probabilities in the network when new data are available[25,30,31]. BBN also deals with prediction, deviation detection, and optimization based on very subjective judgement[32]. To compare with other risks assessment methods like Markov chains, artificial neural networks (ANNs), Monte Carlo simulation, case-based reasoning (CBR), and system dynamics, the BBN has great advantages regarding simplicity to use by the practitioners, and accuracy level on available size of data[25]. Thus, use of fuzzy logic in Bayesian belief network will provide better understanding and evaluation of risks in power plant project.

3. Fuzzy-Bayesian risk assessment model

The new model for risk assessment is the combination of fuzzy logic based group decision-making process and Bayesian belief network. In this model, the judgements of a group of experts are captured by fuzzy comprehensive group decision-making process, which provides the prior probability as risk likelihood and conditional probability as risk consequence. These probabilities are the input variables of the Bayesian belief network for representing the causal relationships among the risks in different work packages of power plant projects. The following sections briefly introduce the basic steps of the model:

3.1. Fuzzy group decision-making process

This process is adapted from Tavakkoli-Moghaddam et al.[33]. The process provides the level of risk likelihood, and consequence, which are the two major components for finding the level of a particular risk. It has the following steps to accommodate group decision for finding the likelihood and consequence of a particular risk.

a. A fuzzy decision matrix, DM (r=1,2,3,….,k), for an individual expert regarding the risk likelihood of occurrence, and consequence of risk as cost impact, is constructed separately. The structure of the decision matrix (DM) is shown in equation 1. In the following matrix, $DM^r_{RL/C}$ is the decision matrix of the respondent r in terms of risk likelihood (RL) and consequence (C) respectively, SR_i means i^{th} sub-factor of risk, WP_j means j^{th} work package, and elements of the matrix $\tilde{x}^r_{ij}$ represents the fuzzy numbers answered by the respondents. The fuzzy number will be found as qualitative terms like Extremely High (EH), Very High (VH), High (H), Moderate (M), Low (L), Very Low (VL), and Extremely Low (EL) from the answer of risk likelihood or consequence of i^{th} risk in j^{th} work package.

$$DM^{r}_{RL/C} = \begin{array}{c} \\ SR_1 \\ SR_2 \\ \dots \\ SR_i \\ \dots \\ SR_m \end{array} \begin{array}{c} \begin{array}{cccccc} WP1 & WP2 & \dots & WPj & \dots & WPn \end{array} \\ \begin{bmatrix} \bar{x}^r_{11} & \bar{x}^r_{12} & \dots & \bar{x}^r_{1j} & \dots & \bar{x}^r_{1n} \\ \bar{x}^r_{21} & \bar{x}^r_{22} & \dots & \bar{x}^r_{2j} & \dots & \bar{x}^r_{2n} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \bar{x}^r_{i1} & \bar{x}^r_{i2} & \dots & \bar{x}^r_{ij} & \dots & \bar{x}^r_{in} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \bar{x}^r_{m1} & \bar{x}^r_{m2} & \dots & \bar{x}^r_{mj} & \dots & \bar{x}^r_{mn} \end{bmatrix} \end{array} \quad (1)$$

b. The qualitative terms (i.e. EH, to EL) in the matrix are transformed into fuzzy triangular number following the Table 1:

Table 1.Level of risk likelihood or consequence, corresponding fuzzy number, and range of crisp number[34]

Level of risk likelihood/consequence	Fuzzy triangular number (FTN)	Crisp number range
Extremely high	90, 100, 100	90 to 100
Very high	70, 90, 100	80 to <90
High	50, 70, 90	70 to <80
Moderate	30, 50, 70	50 to <70
Low	10, 30, 50	30 to <50
Very low	0, 10, 30	10 to <30
Extremely low	0, 0, 10	0 to <10

c. *The elements of the matrix, i.e., FTN is shown in Table 1, are multiplied by the weight of the individual expert (w_i) following fuzzy multiplication rule to get weighted elements of the matrix. The equation is as follows:*

$$(DM^{r}_{RL/C})_w = w_i \otimes (\bar{x}^r_{ij})_L, w_i \otimes (\bar{x}^r_{ij})_M, w_i \otimes (\bar{x}^r_{ij})_U \quad (2)$$

Here, L, M, and U mean the lowest, moderate, and highest possible number of FTN, and the symbol $\otimes$ indicates fuzzy multiplication. The expert's weight (w_i) depends on his/her academic qualification, professional position, year of experience in construction projects, and year of experience particularly at risk management in the construction field.

d. All the matrices for a group of experts are transformed into one single matrix following the fuzzy arithmetic average.

Elements of group matrix=

$$\bar{x}^G_{ij} = \frac{1}{k}\sum_{r=1}^{k} x^r_{ij} \otimes w_r = (\frac{1}{k}\sum_{r=1}^{k} x^r_{ij} \otimes w_r)_L, (\frac{1}{k}\sum_{r=1}^{k} x^r_{ij} \otimes w_r)_M, (\frac{1}{k}\sum_{r=1}^{k} x^r_{ij} \otimes w_r)_U \quad (3)$$

e. The elements of the group matrix are defuzzified by the following equation[35]:

$$\bar{x}^r_{ij} = \frac{L + 4M + U}{6} \quad (4)$$

This equation equation provides a crisp number of an individual risk likelihood or consequence. Then, the third column of Table 1is used to define the crisp number into the corresponding level of risk likelihood or consequence.

f. Finally, fuzzy if-then rules between the risk likelihood of occurrence and consequence presented in Table 2 are applied to finding the level of risk.

Table 2. Fuzzy if-then rules between risk likelihood of occurrence and consequence

Level of Risk		Consequences of the risk factor						
		EL	VL	L	M	H	VH	EH
Likelihood of the risk factor	EL	EL	EL	EL	EL	EL	EL	EL
	VL	EL	VL	VL	VL	VL	L	L
	L	EL	VL	L	L	L	M	M
	M	EL	VL	L	M	M	M	H
	H	EL	VL	L	M	H	H	H
	VH	EL	L	M	M	H	VH	EH
	EH	EL	L	M	H	H	EH	EH

3.2. Bayesian belief network (BBN)

In Bayesian belief network, there are two types of probabilities, such as prior probability, and conditional probability. The risk likelihood of an independent risk is considered as prior probability and the consequence of an independent risk or any preceding risk onto the succeeding risk is considered as the conditional probability. Thus, the nodes of the Bayesian belief network represent prior probabilities and the edges (arrows) among the nodes represent conditional probabilities. The combined result of these two probabilities gives the probability of succeeding or dependent risk. For example, prior probability of A_i (independent or preceding risk) is $P(A_i)$, normalized probability of A_i is $P(A_i^n)$, and the conditional probability of B (i.e., dependent risk) given that A_i is given by $P(B \mid A_i)$, then joint probability, and the probability of dependent risk is as follows:

$$\text{Probability of Dependent risk} = P(B) = \sum_{i=1}^{n} P(B \cap A_i) \tag{5}$$

$$\text{Joint Probability} = P(B \cap A_i) = P(A_i^n) \times P(B|A_i) \tag{6}$$

$$\text{Normalized Probability} = P(A_i^n) = \frac{P(A_i)}{\sum_{i=1}^{n} P(A_i)} \tag{7}$$

Here, the prior probabilities of the risks influencing other risk are necessary to become one[36]. Because, Jaynes[37] recommended that computing the probability distribution of a dependent variable over different alternative outcomes, it is necessary to comply with the principle of maximum entropy (ME), i.e., the following equation should be satisfied:

$$\sum_{i=1}^{n} P(A_i^n) = 1, i = 1,2,3,........, n \tag{8}$$

In this study, the respondents have freedom to choice the probability from a qualitative range like Extreme (Ex) to None (N) which will be then transferred into fuzzy triangular probabilistic numbers shown in Table 3. According to the above equation, the probability of all the variables is normalized to make the sum as one. This study uses the notation $P(A_i^n)$ as normalized probability where the sum of the probability for all i (=1, 2, 3,……,n) is one.

Table 3.Level of risk likelihood or consequence and corresponding probabilities[38,39]

Level of risk likelihood/consequence	Fuzzy triangular number for probability		
	Lower least (L)	Most likely (M)	Upper least (U)
Extremely high	0.9	1	1
Very high	0.7	0.9	1
High	0.5	0.7	0.9
Moderate	0.3	0.5	0.7
Low	0.1	0.3	0.5
Very low	0	0.1	0.3
Extremely low	0	0	0

4. An example of assessing cost overrun risk by using the model

The Figure 1 shows an example of the proposed risk assessment model. A panel of five experts were asked to score the level of risks for the independent risk factors (i.e. the risk factors which have no parents) in terms of extremely high (EH), very high (VH), high (H), moderate (M), low (L), very low (VL), and extremely (EL). Again they were asked to establish the relationship among the risks and their level of significances (impacts) onto succeeding risks following same qualitative terms i.e. EH to VL. Then, fuzzy comprehensive group decision-making process is used to accommodate the judgments of the group of experts finding the levels of independent risks and the consequences of preceding risks onto succeeding risks in the networks. The Bayesian belief network method is used for quantifying the probability of the dependent risks. The two components of the Bayesian belief method are prior probability and conditional probability, which is found successively from the risk levels of preceding risks and the consequence levels of the preceding risks onto succeeding risks calculated by fuzzy comprehensive group decision-making approach.

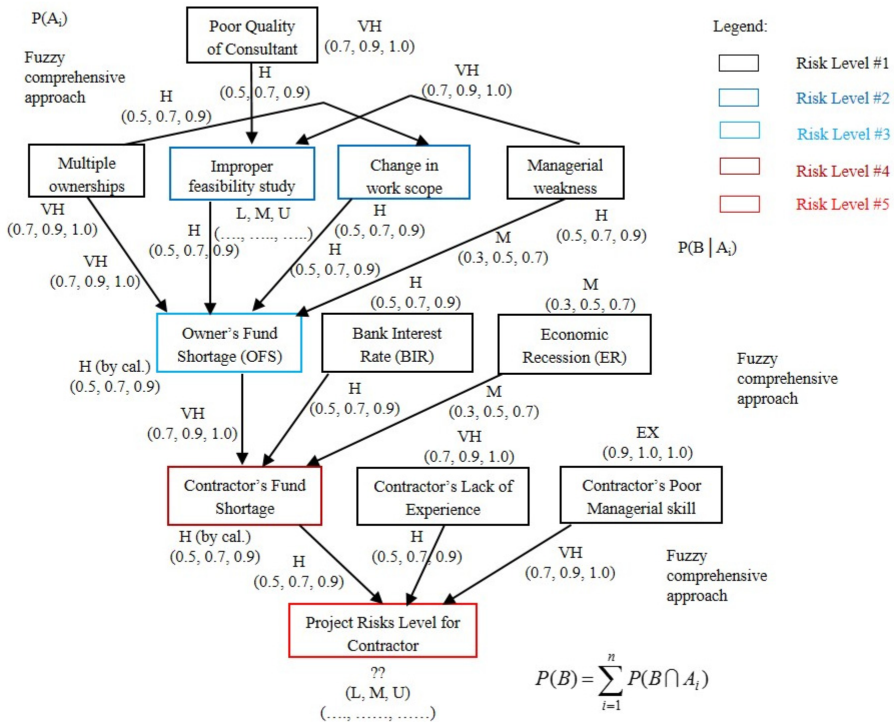

Fig. 1. An example of fuzzy Bayesian belief networks model for risk assessment

In the presented example, there are five hierarchy levels of risks, which are shown as different colors and connected in the networks. The risks “poor quality of consultant”, and “managerial weakness” are independent risks and considered as the risks of level 1 (black colored box). Both of these risks have a direct impact on “improper feasibility study”, which falls into risk level 2 (blue colored box). The Fuzzy comprehensive approach is applied to find the levels of these risks as well as the consequence of these risks onto improper feasibility study based on experts’ judgments. The risk “poor quality of consultant” is recognized as a very high-risk, and “managerial weakness” is identified as high-risk. Besides, the former risk has high impact and later has very high impact influencing the risk “improper feasibility study” (Fig. 1). Table 3 shows that the fuzzy triangular probability numbers for very high and high risk levels are (0.7, 0.9, 1.0) and (0.5, 0.7, 0.9) respectively. Now, dependent risk “improper feasibility study” has prior probabilities of two preceding risks (i.e., risk levels of poor quality of consultant, and managerial weakness) and conditional probabilities, i.e., consequence levels of poor quality of consultant, and managerial weakness onto this risk. Applying Bayesian belief theory mentioned above (equation 5 to 8), the risk level of the improper feasibility study is found as high (0.58, 0.79, 0.95). Similarly, if the process propagates to the higher risk levels (level 3 and 4), it provides high-level of risk for “owner’s fund shortage”, and “contractor’s fund shortage”. Following the same procedures, the project risk level for the contractor identifies as high-level with probability (0.54, 0.74, 0.93).

5. Conclusion

Cost overrun in power plant project is a frequent global problem. Inaccurate estimation during preliminary budgeting of the project is mainly responsible for this issue. Improper risks assessment is considered as one of the critical causes of estimation inaccuracy. Addressing the cost overrun risks in estimation process of a power plant project is essential and significant to increase the accuracy of cost estimation, which subsequently reduces cost overrun. To reduce the cost overrun scenario in power plant project, a model for proper risk assessment is timely and significant. This study aims to develop a risk assessment model by the combination of fuzzy logic and Bayesian belief networks. Fuzzy logic is appropriate to define the project risks and uncertainties found by the judgment of domain experts, and BBN has the advantage to capture the complex relationship among the risks. The BBN also provides opportunities to update the model getting available information. Thus, the proposed fuzzy-BBN model for risk assessment provides more understanding about the complex relationship of risks in power plant projects, where risks assessment mostly depends on experts’ judgments. It also assists risk analysts and cost estimators to find potential risks for providing more realistic budget and reducing cost overrun in power plant and other similar complex projects. Finally, it is recommended to extend this study applying the proposed model in more extensive work as a further research in the risk assessment of power plant projects for the justification of the model in practice.

References

1. B. K. Sovacool, A. Gilbert, and D. Nugent, “An international comparative assessment of construction cost overruns for electricity infrastructure,” *Energy Res. Soc. Sci.*, vol. 3, pp. 152–160, 2014.
2. IHS, “IHS Costs and Strategic Sourcing. Power Capital Costs Index and European Power Capital Costs Index. Available at https://www.ihs.com/info/cera/ihsindexes/index.html,” 2014. .
3. M. Bosch-Rekveldt, Y. Jongkind, H. Mooi, H. Bakker, and A. Verbraeck, “Grasping project complexity in large engineering projects: The TOE (Technical, Organizational and Environmental) framework,” *Int. J. Proj. Manag.*, vol. 29, no. 6, pp. 728–739, 2011.
4J. Odeck, M. Welde, and G. H. Volden, “The impact of external quality assurance of costs estimates on cost overruns: Empirical evidence from the norwegian road sector,” *Eur. J. Transp. Infrastruct. Res.*, vol. 15, no. 3, pp. 286–303, 2015.
5. Y. Frimpong, J. Oluwoye, and L. Crawford, “Causes of delay and cost overruns in construction of groundwater projects in a developing countries; Ghana as a case study,” *Int. J. Proj. Manag.*, vol. 21, no. 5, pp. 321–326, Jul. 2003.
6. J. O. Dada and G. O. Jagboro, “An evaluation of the impact of risk on project cost overrun in the Nigerian construction industry,” *J. Financ. Manag. Prop. Constr.*, vol. 12, no. 1, pp. 37–44, 2007.
7. D. Baloi and A. D. F. Price, “Modelling global risk factors affecting construction cost performance,” Int. J. Proj. Manag., vol. 21, no. 4, pp. 261–269, May 2003.
8. K. S. Rebeiz, “Public–Private Partnership Risk Factors in Emerging Countries: BOOT Illustrative Case Study,” J. Manag. Eng., vol. 28, no. April, pp. 203–211, 2012.
9. T. R. Browning, “Managing complex project process models with a process architecture framework,” Int. J. Proj. Manag., vol. 32, no. 2, pp. 229–241, 2014.

10. K. B. Salling and S. Leleur, “Accounting for the inaccuracies in demand forecasts and construction cost estimations in transport project evaluation,” Transp. Policy, vol. 38, pp. 8–18, 2015.
11. E. E. Ameyaw, A. P. C. Chan, O.-M. De-Graft, and E. Coleman, “A fuzzy model for evaluating risk impacts on variability between contract sum and final account in government-funded construction projects,” J. Facil. Manag., vol. 13, no. 1, pp. 45–69, 2015.
12. L. A. Vidal, F. Marle, and J. C. Bocquet, “Measuring project complexity using the Analytic Hierarchy Process,” Int. J. Proj. Manag., vol. 29, no. 6, pp. 718–727, 2011.
13. G. Abdollahzadeh and S. Rastgoo, “Risk Assessment in Bridge Construction Projects Using Fault Tree and Event Tree Analysis Methods Based on Fuzzy Logic,” ASCE-ASME J. Risk Uncert. Engrg. Sys., Part B Mech. Engrg., vol. 1, no. 3, p. 031006, 2015.
14. M. M. G. Elbarkouky, N. B. Siraj, and A. R. Fayek, “Fuzzy Contingency Determinator © A Fuzzy Arithmetic-Based Risk Analysis Tool for Construction Projects,” IEEE, 2015.
15. A. Eriksson, “Fuzzy risk assessment for construction projects - With focus on farm-based grain drying facilities,” Swedish University of Agricultural Sciences, 2015.
16. A. Salah, “Fuzzy Set-based Risk Management for Construction Projects,” Concordia University, 2015.
17. M. Eybpoosh, I. Dikmen, and M. T. Birgonul, “Identification of risk paths in international construction projects using structural equation modeling,” J. Constr. …, vol. 137, no. 12, pp. 1164–1175, 2011.
18. V. Khodakarami and A. Abdi, “Project cost risk analysis: A Bayesian networks approach for modeling dependencies between cost items,” Int. J. Proj. Manag., vol. 32, no. 7, pp. 1233–1245, 2014.
19. H. S. Vander and S. Knapp, “A multi-layered risk exposure assessment approach for the shipping industry,” Transp. Res. Part A Policy Pract., vol. 78, pp. 21–33, 2015.
20. H. Abdul-Rahman, C. Wang, and Y. L. Lee, “Design and Pilot Run of Fuzzy Synthetic Model (Fsm) for Risk Evaluation in Civil Engineering,” J. Civ. Eng. Manag., vol. 19, no. 2, pp. 217–238, 2013.
21. H. Subramanyan, P. H. Sawant, and V. Bhatt, “Construction Project Risk Assessment: Development of Model Based on Investigation of Opinion of Construction Project Experts from India,” J. Constr. Eng. Manag., vol. 138, no. 3, pp. 409–421, 2012.
22. T. Lyons and M. Skitmore, “Project risk management in the Queensland engineering construction industry : a survey,” Int. J. Proj. Manag., vol. 22, no. November 2002, pp. 51–61, 2004.
23. J. Ren, I. Jenkinson, J. Wang, D. L. Xu, and J. B. Yang, “An Offshore Risk Analysis Method Using Fuzzy Bayesian Network,” J. Offshore Mech. Arct. Eng., vol. 131, no. 4, pp. 1–28, 2009.
24. I. Dikmen, T. Birgonul, and M. Eybpoosh, “Tracing Risk Paths in International Construction Projects: a Case Study,” Proc. MISBE2011 - Int. Conf. Manag. Innov. a Sustain. Built Environ., no. June, pp. 1–12, 2011.
25. P. C. Li, G. H. Chen, L. C. Dai, and L. Zhang, “A fuzzy Bayesian network approach to improve the quantification of organizational influences in HRA frameworks,” Saf. Sci., vol. 50, no. 7, pp. 1569–1583, 2012.
26. P. Weber, G. Medina-Oliva, C. Simon, and B. Iung, “Overview on Bayesian networks applications for dependability, risk analysis and maintenance areas,” Eng. Appl. Artif. Intell., vol. 25, no. 4, pp. 671–682, 2012.
27. S. Tesfamariam, “Risk assessment of bridges using Bayesian belief network : with consideration of seismic and aging,” 2013.
28. N. Khakzad, F. Khan, and P. Amyotte, “Safety analysis in process facilities: Comparison of fault tree and Bayesian network approaches,” Reliab. Eng. Syst. Saf., vol. 96, no. 8, pp. 925–932, 2011.
29. U. B. Kjærulff and A. L. Madsen, Bayesian Networks and Influence Diagrams. 2008.
30. J. H. Sigurdsson, L. a. Walls, and J. L. Quigley, “Bayesian belief nets for managing expert judgement and modelling reliability,” Qual. Reliab. Eng. Int., vol. 17, no. November 2000, pp. 181–190, 2001.
31. J. T. Christian, “Geotechnical Engineering Reliability: How Well Do We Know What We Are Doing?,” J. Geotech. Geoenvironmental Eng., vol. 130, no. 10, pp. 985–1003, 2004.
32. N. Khakzad, F. Khan, and P. Amyotte, “Quantitative risk analysis of offshore drilling operations: A Bayesian approach,” Saf. Sci., vol. 57, pp. 108–117, 2013.
33. R. Tavakkoli-Moghaddam, S. M. Mousavi, and H. Hashemi, “A Fuzzy Comprehensive Approach for Risk Identification and Prioritization Simultaneously in EPC Projects,” in Risk Management in Environment, Production and Economy, M. Savino, Ed. INTECH Open Access Publisher, 2011.
34. Y.-C. Kuo and S.-T. Lu, “Using fuzzy multiple criteria decision making approach to enhance risk assessment for metropolitan construction projects,” Int. J. Proj. Manag., vol. 31, no. 4, pp. 602–614, 2013.
35. M. Abdelgawad and A. R. Fayek, “Risk Management in the Construction Industry Using Combined Fuzzy FMEA and Fuzzy AHP,” J. Constr. Eng. Manag., vol. 136, no. 9, pp. 1028–1036, 2010.
36. B. Song, C. Lee, and Y. Park, “Assessing the risks of service failures based on ripple effects : A Bayesian network approach,” Intern. J. Prod. Econ., vol. 141, no. 2, pp. 493–504, 2013.
37. E. T. Jaynes, “Prior Probabilities,” IEEE Trans. Syst. Sci. Cybern., vol. 4, no. 3, pp. 227–241, 1968.
38. A. Idrus, M. Fadhil Nuruddin, and M. A. Rohman, “Development of project cost contingency estimation model using risk analysis and fuzzy expert system,” Expert Syst. Appl., vol. 38, no. 3, pp. 1501–1508, 2011.
39. A. Valipour, N. Yahaya, N. Md Noor, S. Kildienė, H. Sarvari, and A. Mardani, “A fuzzy analytic network process method for risk prioritization in freeway PPP projects: an Iranian case study,” J. Civ. Eng. Manag., vol. 21, no. 7, pp. 933–947, 2015.